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Automatic Indonesian's Batik Pattern Recognition Using SIFT Approach

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Abstract

Batik is a traditional clothwith unique patterns applied to fabric using a wax-resist dyeing technique. Aside from preserving this rich cultural heritage, the automated recognition of Batik patterns would enable many interesting applications. This paper introduces an approach to batik pattern recognition using the Scale Invariant Feature Transform (SIFT) as a feature extraction method. The challenging issues that arise are due to the highly symmetrical and repetitive properties of batik patterns. The Hough transform, as an evidence-based method of object detection, is applied to handle mismatched keypoints resulting from symmetrical and repetitive patterns of batik. On a collection of 120 batik images generated from 20 basic batik patterns, the proposed method showsan improvement over the original SIFT matching method with an equal error rate of 8.47%.

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*Keywords:*Batik; motif; SIFT; voting; Hough transform

1. Introduction

Batik is a famous instance of cultural heritage from Indonesia. Batik, as a traditional cloth, is made using a manual wax-resist dyeing technique[1,2]. The word Batik comes from the Javanese language and consists of two parts namely "*Mbat*" and "*Titik*", and means to make a "*titik*" (dot)[3]. This is achieved using a "*canting*", a pen-like device to draw the batik pattern in wax, and "*malam*"(beeswax)[4].Fabric coloring using *malam* is intended to cover up or

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block the entry of dyes into the pattern. There are two main batik motifs: geometric and non-geometric. The geometric patterns are recognizable due to the symmetry and repetition in horizontal, vertical, and diagonal directionsthat form angles between shapes. On the other hand, the non-geometric patterns typically do not exhibit such symmetrical patterns. Several geometric patterns are very widely used, such as *ceplok*, *kawung*, *parang*, *lereng*, and *nitik*. As for the non-geometric patterns,the major patterns include*Lung-lungan*, *Semen*, *Pagersari*, and *TaplakMeja*. Each pattern has its own particular variety and distinctive features.

Generally, batik patterns are limited to ornaments and stripes. The main reason is due to the difficulty of weaving detailed and irregular ornamental compositions into the cloth. Batik patterns are divided into several groups of designs template classes. Each class has hundreds of variations within them. Even though similarities between the batik patterns can be identified, nevertheless there are slight differences in detail, such as the use of color. Batik pattern recognition has been developed based on high level features of batik that invariant to scale, rotation, and other transformations.

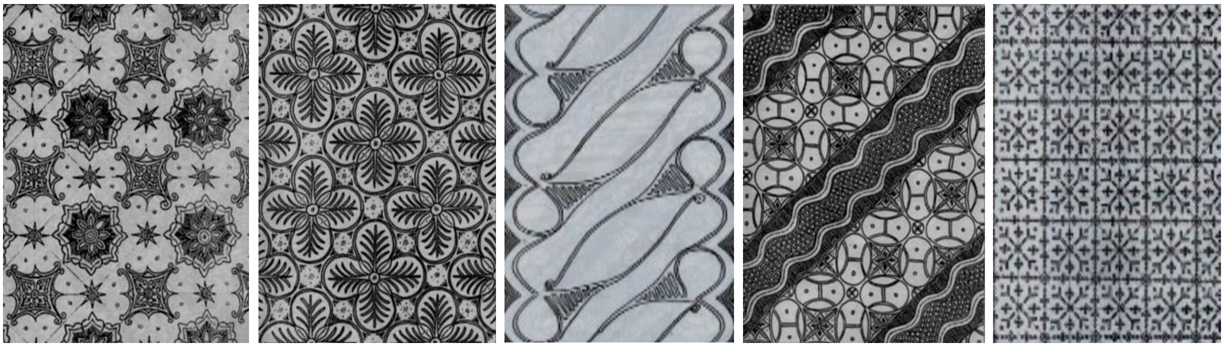

Fig. 1. Geometric Pattern [3]

Batik is one of Indonesia's rich cultural heritage treasures, and many efforts have been made to preserve and promote it. It is important that people are involved in these preservation and promotion efforts.The growth of the batik industry has created a multiplier effect for small and medium enterprise industries in Indonesia. In the computer vision area, documentation of batik in large databases can be implemented as a digital repository system due to the large variety of batik pattern.This study is a preliminary research of batik pattern recognition. Our main goal is to develop a digital repository system for batik motifs which contains both geometric and non-geometric pattern in a large scale database.

Some approaches to object recognition have proved to be robust to noise addition, compression, and retouching, however only few of them are effectively reliable over multiple objects geometrical disruption such as rotation, scaling, and translation.Various algorithms based on keypoint descriptors are presented. Lowe developed a scale invariant feature transform (SIFT) method for extracting distinctive invariant features from images that can be used to perform reliable matching between different views of an object or scene[5]. SIFT is one of the best algorithms for the extraction of the feature points. Speeded-up Robust Features (SURF) is a faster alternative than SIFT[5,6].

The typical properties of batik cloth patterns are the very high prevalence of symmetrical and repetitive structures between sections in one object. Therefore, the symmetrical property and multiple occurrences of batik pattern makes the recognition process much more complicated, and presents a challenge for computer vision researchers. This characteristic is illustrated in Fig. 2. This issue has received considerable critical attention in this study. Despite many batiks sharing the same motif, they may be different in terms of position, size, and direction. This condition may lead to the false recognition of batik patterns. Therefore, in order to classify a batik cloth using a particular motif, a robust method is required to overcome this problem. The method has to resolve the problem of suitable features that will be used for recognition which is invariant to scale, rotation, translation and repetitive objects.

Furthermore, in the case of regular patterns like batik, it is the most challenging problem of texture analysis to determine the primitive object from batik pattern. This primitive object will be used to classify the batik pattern.

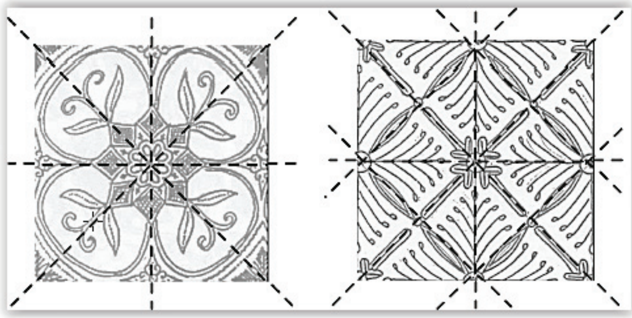

Fig.2. The symmetrical section of batik pattern

The main objectives of this paper is to examine and to evaluate SIFT features based on voting using the Hough transform for object recognition in batik patterns. Furthermore, it seeks to clarify whether the proposed method will improve the rate of recognition accuracy.

This paper is organized in the following way. In Section 2, we present previous work relevant to object recognition. Section 3 discusses the feature extraction method. Section 4 presents the proposed method for batik pattern recognition. Section 5 presents the experimental scenario. Section 6 describes the experimental results and discusses the findings, before a conclusion in Section 7.

2. Background and Related Work

Recent attention has focused on the classification and retrieval of batik image based on texture features. Nurhaida[7]presents a texture-based batik motif identification method. The highest performance of classification accuracy reached nearly 80% from Grey Level Co-occurrence Metrics method. In a study of batik image retrieval that applied edge feature orientation combined with micro structure descriptors for enhancing retrieval, Minarno[8]obtained the best performance of 74% precision and 89% recall. Research by Rangkuti [9] reportedapplying Canny edge detection on the input image, wavelet transform as texture features and invariant moment as shape features. The results achieved optimal precision inthe region of 90% to 92%. SIFT and Invariant Generalized Hough Transform (IGHT) are compared regarding the performance for batik cloth classification using a particular motif[10]. The best accuracy obtained from SIFT reaches around 80% to 87%. Therefore, it is concluded that SIFT is appropriate for batik motif classification. Research by Bouty[11]discusses the implementation of Invariant Generalized Hough Transform method for calculating the rotation angle of batik motifs. The extraction of the accumulator array is performed using the hillclimbing and combined with a low pass filter for smoothing. This implementation gained better accuracy to find the object occurrence position with a value of precision and recall by 42% and 94%. In this study, we perform batik pattern recognition in different way. Based on intricate knowledge of batik pattern, we recognizedeach object pattern consecutively from a batik image and matched it against templates in a database.

There have been a number of reported researches involving multiple object detection. Research by Aragon and Siebert[12] employed Hough space for representingmultipleinstances of the same object class. It allows their localization and detection within acluttered scene under occlusion and self-occlusion. The image feature representation affected performance of an objectrecognitionsystem. The main weakness of the Hough transform is that it treats object properties independently through the voting mechanism. Yarlagadda et. al[13]has overcome this weakness by combining independent features based on sliding windows and votes using probabilistic Hough voting. Rabin et.al[14]utilized SIFT-like descriptors and Earth Mover's Distance to reduce time complexity. The matching procedure is applied to discover multiple occurrences of an object.

Based on the assumption that the same texture can look significantly different at different scales, research by Ardizzone et.al[15]defines thescale of texture fromthe size of the basic elements by distribution of the interest points into the image using Keypoint Density Maps. Research by Chen and Hsieh[16]improved the SIFT matchingto gain a fast image retrieval scheme that transforms the SIFT features to binary representations.

3. Feature Extraction Method

3.1. Scale Invariant Feature Transform

The localization of reference positions in corner objects, called interest points, is important information that is required for real applicationssuch as object tracking and image alignment[17]. However, there is a drawback from the utilization of corner points to find similar objects. Information provided by corner points is not adequate to represent the object. Corner points only provide information about position and the power of each corner point. Consequently, Lowe proposed an image feature named the Scale Invariant Feature Transform(SIFT)[18]. It represents an object using regional descriptors around interest points to perform object recognition. The following main steps to extract invariant features using SIFT are:

a. Scale-space extrema detection.
   The candidate keypoints can be obtained by detecting extrema from Difference of Gaussian (DoG) pyramid which is an approximation of Laplace of Gaussian (LoG).
b. Keypoints localization.
   In order to obtain stable keypoints, three processes are applied in this step. The first process is to find the accurate location of keypoints using 3rd order Taylor polynomial; the second process is eliminating keypoints that have low contrast; and the third process is to eliminate the keypoints which are in the edge using principal curvature.
c. Orientation assignment.
   The orientation of a keypoint will be calculated based on the gradient and orientation of a region around the keypoint. A keypoint may have more than one orientation.
d. Keypoint descriptor.
   The orientation and gradient magnitude are calculated at each point in the window. An orientation histogram which represents eight cardinal directions are calculated for each sub region based on gradient magnitude. The keypoint descriptor consists of 128 elements which are from 16 sub regions where each sub regions consists of 8 features.

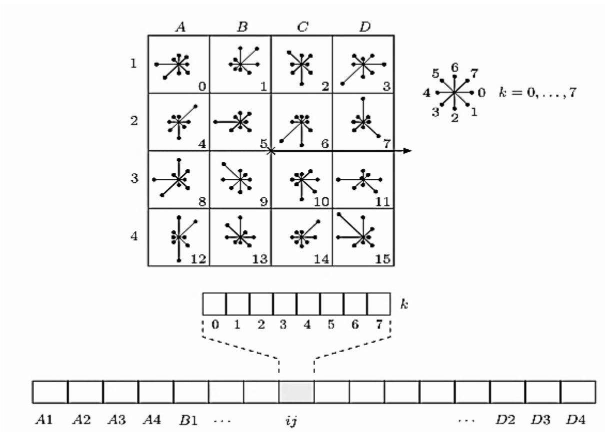

Fig. 3. SIFT descriptor structure[17]

This process is shown in Fig 3. The scale and orientation of each keypoint is obtained from a patch based around the centre position of keypoint. The size of the keypoint is determined by the scale of the octave in which it has been detected. The size of the keypoint region is a Gaussian window which is set to 1.5 times bigger than the Gaussian filter used in the smoothed image where the keypoint center is detected. The dominant gradient direction around the centre keypoint will be used to determine the orientation of the keypoint itself. A histogram of gradient directions with 36 bins is created, where each bin covers 10 degrees. The gradient direction θ of each sample position is weighted by the gradient magnitude *m* and a

Gaussian-weighted circular window with a *sigma* 1.5 times bigger than the scale of the detected keypoint:

$$m(x,y) = \sqrt{(L\,(x+1,y) - L(x-1,y))^2, (L(x,y+1) - L(x,y-1))^2}(1)$$

$$\theta(x,y) = arctan\,\frac{L(x,y+1)-L(x,y-1)}{L\,(x+1,y)-L(x-1,y)}(2)$$

Where:

L(x, y)	=	the pixel value in the position x, y of the Gaussian-blurred image L
m(x,y)	=	gradient magnitude
θ(x,y)	=	direction

The dominant gradient directions are considered as those above 80% of the highest histogram maximum. Sometimes more than one dominant orientation is formed and more than one SIFT detection is assigned to the same position of the image.

3.2. Voting Hough Transform

Voting the features of object poses using the Hough Transform reveals the consistent interpretations for batik recognition based on evidence within an image. Each SIFT keypoint specifies 4 parameters i.e. *x translation, y translation,scale*, and *orientation* parameter values from the template images. Voting of each keypoint for the set of object poses is performed to determine the keypoint's location, scale and orientation consistently. Research by Lowe[18]suggestedthat objects could be reliably identified with as few as 3 features to maximize the performance of object recognition for small or highly occluded objects. Bins that accumulate at least 3 votes are identified as candidate object/pose matches. If fewer than 3 points are found then the object match is rejected. In this research, to ensure the validity of candidates matched keypoint, the voting Hough transform is applied as a post processing. The mismatched keypoint will be eliminated due to selection of the highest value in the Hough accumulator array. Post processing using voting Hough transform will generate the hypotheses for transformation object. It will indicate the object pose in query image. This configuration will be found as the highest value of the Hough accumulator array.

4. The Proposed Batik Motif Recognition Methodology

We define the batik object recognition task as trying to find all instances of a particular pattern, or template, in a digital image. It is performed by comparingthe information of region descriptors detected in a template image to a query image. The recognition process is carried out through pairwise matching between the corresponding descriptorsof the interest points within both the template and query image. The two main steps involved are feature extraction and feature matching[19]. Image features are first extracted from the query and template image. Those feature descriptors will subsequently be used for matching several images of an object in a query image compared to template images. Fig. 4 shows an illustration of the proposed methodology in this study.

The proposed methodology is based on the Scale Invariance Feature Transform (SIFT) by David Lowe[18]. The main idea is to find extreme points in an image and then to construct regional point descriptors that are invariant to rotation and scalecalled keypoints. Each keypoint is very distinctive. In order to recognize Batik patterns in query images, the number of matched keypoints will be used as a measurement indicator. The similarity between descriptors from the query and template images are specified with the minimum Euclidian Distance. Lowe suggests a distance ratio threshold of 0.8 between the closest match and the second closest match as a reliable method to discard spurious and false matches.

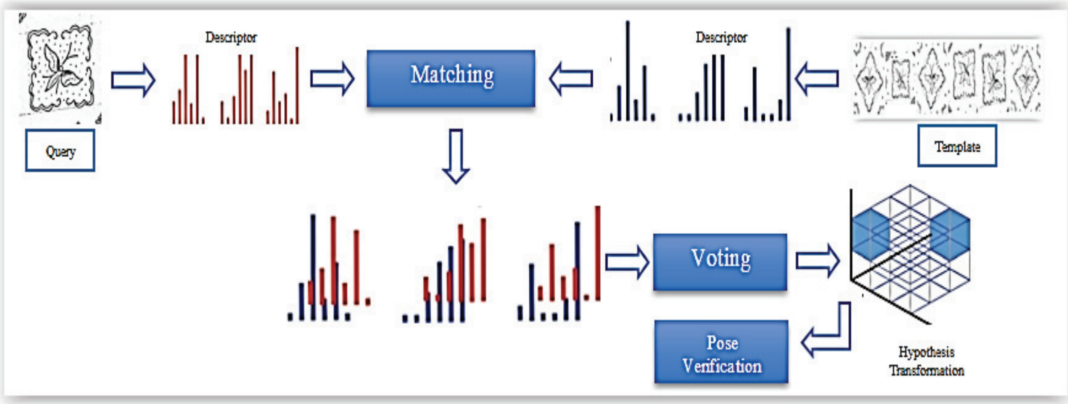

Fig.4. The proposed method

In this study, unlike the original SIFT, the distance ratio threshold will be set at 1.0. In other words, all of the potentially matched keypoints are considered. The matched keypoints are stored as candidate pairs that will be used in the next process. By considering all possible matches, many false hypotheses are considered. Thus, to ensure the validity of candidate matches between keypoints, the Hough transform is applied as an evidence-based process to see which groups of pairs consistently share the same pose, i.e. transformation of translation, rotation, and scale. The mismatched keypoint pairs will be eliminated due to selection of the highest value in the Hough accumulator array. This configuration will be found as the highest value of the Hough accumulator array. Post processing using the Hough transform will generate the various hypotheses for object transformations. It will indicate the object poses in the query image. The mismatched keypoints are possibly more than 90%,which can lead to difficulties in finding the correct object pose[20]. The voting process will eliminate inconsistent geometrical correspondences from the hypotheses in terms of object poses (translation, rotation, and scale).

The steps of the Hough Transform are as follows:

1. Generating parameter space:
   The keypoint a_i in the query image is matched to the keypoint a_i' in the template image. The localization, scale, and orientation of keypoint $a_i$is $x_i, y_i, \sigma_i, \theta_i$ while $x_i', y_i', \sigma_i', \theta_i'$ are for keypoint a_i'. The translation between two keypoints is $(\Delta x, \Delta y) = (x_i' - x_i, y_i' - y_i)$. The scale change between keypoints is $= \frac{\sigma_i'}{\sigma_i}$. The rotation between two features is $\Delta\theta = (\theta_i' - \theta_i)$. So, $(\Delta x, \Delta y, Q\sigma, \Delta\theta)$ is set as the Hough parameter space.
2. Determining appropriate bin sizes:
   If the bin sizes are too wide, the error would be large. However, if the bin sizes are too narrow, the algorithm would be sensitive to noise and cost much time and memory.
3. Voting on the Hough parameter space:
   $(\Delta x, \Delta y, Q\sigma, \Delta\theta)$ is computed for each match and the matching keypoint pair votes in the Hough space. To avoid the boundary effects, the matching keypoint pair votes on the 2 closest bins in each dimension. So, each matching keypoint pair votes on 16 subspaces. The Hough parameter spaces can be realized with the suitable hash function and one-dimensional hash table.

5. Experimental Design

5. 1. Experiment Data Set

The proposed Batik pattern recognition method was evaluated using 20 images of fundamental templates of batik pattern from Samsie[3]. Each pattern has six variations, for a total of 120 images. The example of the data set is shown in Fig.5.There are several numbers of similar batik patternsthat are chosen for the experiment.

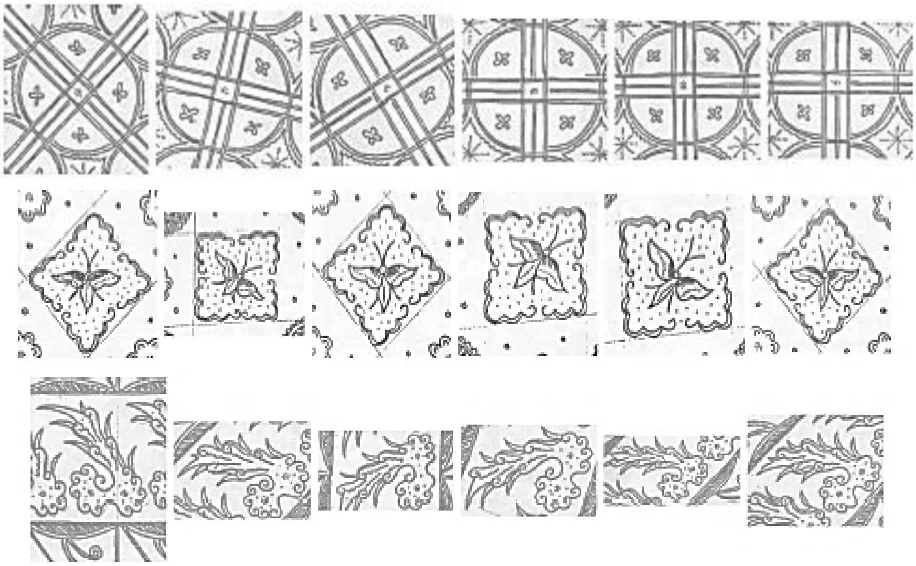

Fig.5. Primitive pattern of batik data

5. 2. Experimental Design

For this study, we compare one basic pattern as a template image against various query images. The value of the Hough accumulator array represents the number of matched keypoints that share the same pose configuration. The highest number of similar keypoint matches based on voting via the Hough transform will be determined as the true object. The proposed Hough-based method will be compared to the regular SIFT approach with Lowe's proposed distance ratio of 0.8. The Equal Error Rate (EER) by Poh and Bengio[21]will be calculatedto measure the performance of the proposed method. The (FNMR) and False Match Rate (FMR) are equal. Based on the value of EER, the optimal threshold can also be considered. The value of FNMR can be calculated by the division of the number of errors in genuine matching to the total genuine matching. On the other hand, the value of FMR can be calculated by comparing the number of errors in imposter matching against the total amount of imposter matching. Genuine matching occurs when the result should indeed be matched, whilst imposter matching occurs when the result should actually not be matched. In the dataset used in this study, there are 300 genuine matches and 6,840 imposter matches.

6. Result and Discussion

The unique properties of symmetry and repetition in Batik patterns creates a unique challenge for matching objects. This leads to many errorsin the matching process using the original SIFT keypoint matching method as proposed by Lowe. The symmetric elements from batik pattern generatea large number ofspuriously mismatched keypoints. The Batik pattern features in local regions can be very similar from each other. As illustrated in Fig. 6 (a), it can be observed that the original SIFT method produces a lot of mismatched keypoints.Hence,it could conceivably behypothesized that the regular SIFT matching cannot be used for batik motif recognition directly. In this study, all of the matched keypoints are captured and stored ascandidate keypoints. Next, these candidates willbe used as input for the Hough voting process. Mismatched keypoints will be eliminated due to selection of the highest value inthe Houghaccumulator array. The valid matched keypoints that are considered are those that share the same configuration for geometric object pose (i.e. scale, rotation and translation). The present results are significant in generating the validmatched keypoints (see Fig. 6. (b)). In contrast to the earlier matching process with the original SIFT matching, this proposed method produced more valid matched keypoints.

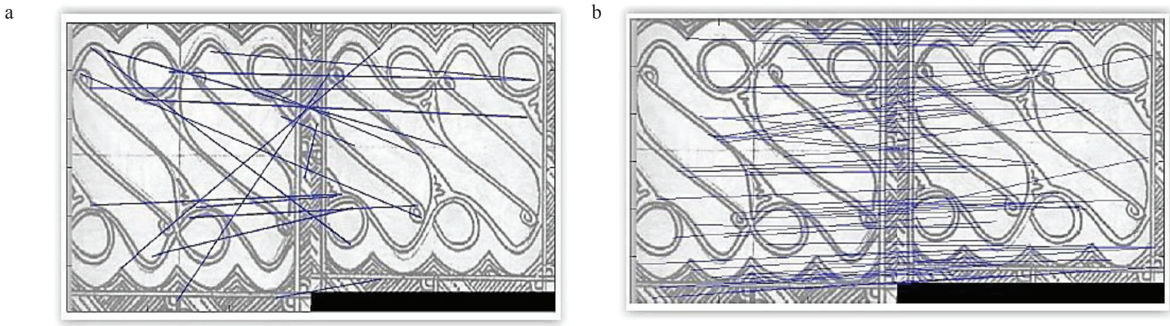

Fig. 6. Matched Keypoint (a) The matched keypoints using regular SIFT method with distant ratio 0.8
(b) The matched keypoints using SIFT and voting Hough transform method with distant ratio 1.0

The results obtained from analysis of FNMR, FMR and EER of the original SIFT approach and the proposed method are shown in Fig. 6 and Fig. 7. The EER for the original SIFT is at 26.60% with threshold of 19 (Fig. 7), while the proposed method is at 8.47% with threshold of 30 (Fig. 8).

From the graphs, it can be seen that the proposed method has better performance than the original SIFT matching method. The error obtained from the proposed method is much lower than the original SIFT approach. By utilizing the Hough transform voting, the matched keypoints are selected by filtering only the matched keypoint that have the same configuration (i.e. scale, rotation and translation). It is interesting to note that the same pattern can generate matched keypointsthat have exactly the same configuration in terms of geometrical pose. In the case of Batik pattern recognition, regular SIFT matching yieldsfewer correct matched keypoints than our proposed method, even though there are a large number of matched keypoints generated from both query and template image.

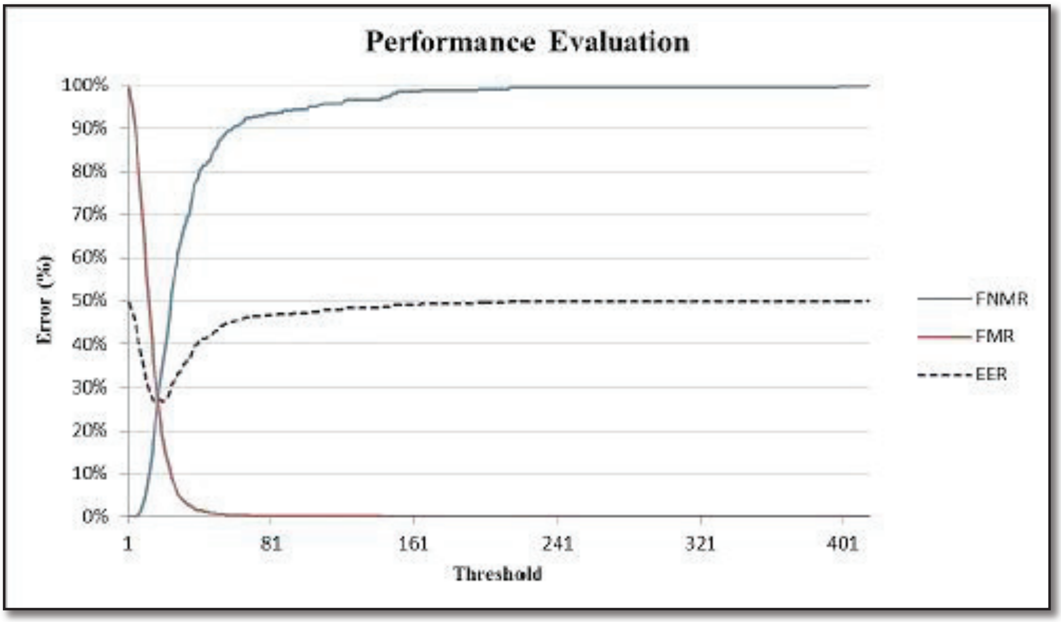

Fig. 7. The performance evaluation of the original SIFT

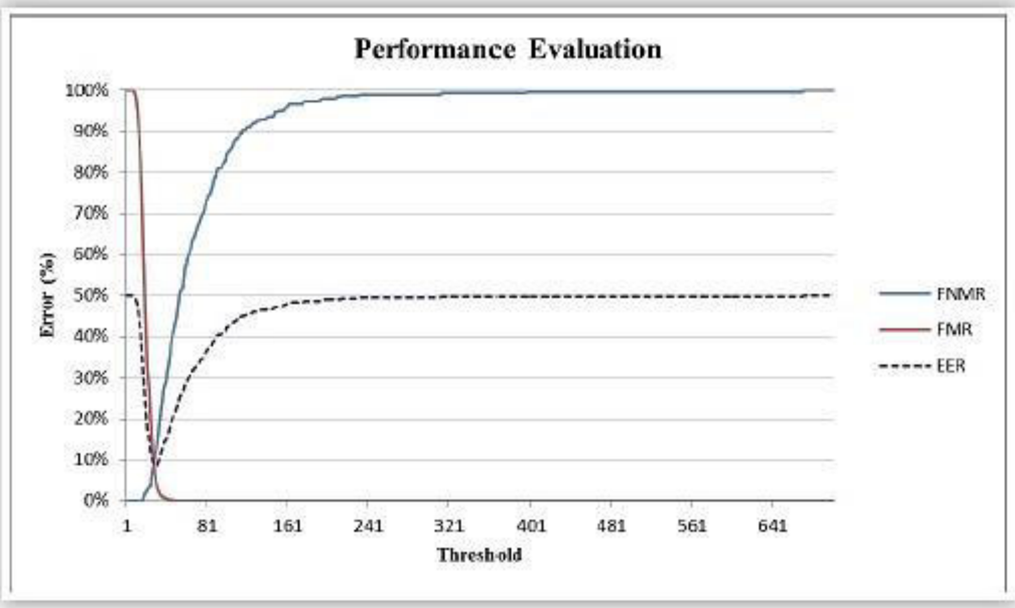

Fig. 8. The performance evaluation of the proposed method

7. Conclusion

The purpose of the current study was to determine the utilization of SIFT and the Hough transform voting process for Batik pattern recognition. The results of the study have shown that the proposed method gainsbetter performance than the original SIFT matching method with 8.47% equal error rate. The Hough transform as a post processing method has an important role to eliminate the mismatched keypoints and to keep the validmatched keypoints. This post processing method is very important since the original SIFT method generates a large number of mismatched keypoints due to the symmetrical and repetitiveness properties of Batikcloth patterns.

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